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Abstract: Although the existing studies questioned the simple positive correlation between the innovation speed and the benefits, they have been widely condemned for lacking empirical evidence. Using the database of patent transfer at the city-scale in China, and distinguishing fast from slow by dividing innovation speed into four levels, this paper attempts answer the question in terms of city economic growth, that is, is faster really better? Panel regression results show that for city economic growth, the speed of technology transfer does not mean that faster is better. In other words, technology transfer that is only maintaining a relatively rapid speed (more than one year and less than two years) can promote city economic growth, although the evidence is weak.

Keywords: technology transfer; innovation speed; Economic effects; Panel regression models; City-scale

1. Introduction

Within this period which some refer to as "the new normal", China's economy is facing downward pressure on growth and requires a new and powerful source of stimulation to face the challenge of transformation and upgrading (Tung, 2016). Among the policy options to foster this new engine of growth are the need to speed up technology transfer on a largescale and to implement an innovation-driven development strategy (Li, 2017). Promoting technology transfer has thus become an important focus not only for policymakers (e.g., on May 09, 2016, the General Office of the State Council released the *Action Plan for Promoting the Transfer of Scientific-Technological Achievements*, and on September 26, 2017, the State Council promulgated the *National Technology Transfer System Construction Plan*) but also among academics (Zhang et al., 2016; Sun and Grimes, 2017).

Research on technology transfer originated from the problems highlighted in the international technology transfer dominated by multinational corporations in the 1960s and 1970s. Therefore, in the early stage of technology transfer research, the academic community was more concerned with international technology transfer. With the increasing scientific capacity of universities and research institutions such as national laboratories, scholars began to pay attention to the issue of technology transfer between universities and enterprises within countries (Etzkowitz and Leydesdorff, 2000; Etzkowitz, 2017; Bozeman, 2000; Link, 2011; Bozeman et al., 2015). In this process of transformation, many scholars believed that the *U.S. Bayh-Dole Act* greatly promoted university technology transfer (Shane, 2004; Aldridge and Audretsch, 2011). Other scholars also discovered that geographic proximity played an important role in technology transfer between regions (Boschma, 2005; Ibert et al., 2015; Marco et al., 2017; Sun and Grimes, 2017).

Through this work, a large number of inter- or intra-regional technology transfer issues (e.g., networks, determinants, effects) predominantly national in scope were

widely revealed (Drivas and Economidou, 2015; Wang et al., 2015; Zhang et al., 2016). A surprising finding which is that different from what is found for research at the organization-level is that databases at the regional level were consistently based on the patent transactions including licensing or transferring (Sun and Cao, 2015; Sun, 2016; Marco et al., 2017; Sun and Grimes, 2017). Unfortunately, so far we have not observed any studies at the city level.

In the literature on innovation, speed is always regarded as a capability that can yield significant competitive advantage for a firm (Sonnenberg, 1993). Rapid innovation can effectively increase the revenue returns (Kessler and Chakrabarti, 1996; Kessler and Bierly, 2002; Allocca and Kessler, 2006; Acur et al., 2010; Shan et al., 2016). Since the development of research on technology transfer, speed has been one of the key dimensions with the purpose of understanding the effects of technology transfer on organizational performance, and has also received a substantial amount of theoretical and empirical attention (Markman et al., 2005; Knockaert et al., 2009; McCarthy and Ruckman, 2017). When there is widespread agreement about a certain theory, there are often some opposing voices suggesting that excessive speed could have a negative impact (Allain et al, 2011; Mauleon et al,2013). However, these contrary views are widely criticized for a lack of definite evidence (Markman et al, 2005; McCarthy & Ruckman., 2017).

In this paper, we provide an empirical analysis of data on patents transfer, in which the licensing channel has been excluded, and we explore this phenomenon at a city-level. Using a sample of 246 cities at prefecture level and above in China and viewing the elapsed time between application and transfer as a surrogate for innovation speed, we posit that technology transfer is positively related to the city economic growth. We then explore the effects of innovation speed in the context of city economic growth.

The remainder of the paper is organized as follows. Section 2 discusses the innovation speed theory based on the literature review. Section 3 introduces the data, describes the explanatory variables used in the empirical analysis and provides some relevant descriptive statistics. Section 4 presents the results, and finally Section 5 concludes with a discussion of the findings, their limitations, and implications for policy and future research.

2. Theoretical background

Tracing the development of innovation speed theory, there are two main lines: one is innovation diffusion theory in sociology and economics, the the other is the product life cycle theory in management.

Diffusion of innovation is a theory that seeks to explain how, why, and at what speed new ideas and technology spread. No one denies that the concept of diffusion was first studied by the French sociologist Gabriel Tarde in late 19th century (Kinnunen, 1996). In his book of *The Laws of Imitation* (1980), the adoption rate of a new idea followed an "*S*-curve" in time, and imitation was considered as an important means of diffusion. In 1943, A study of the adoption of hybrid corn seed in Iowa confirmed that the diffusion of agricultural technology also showed an "*S*-curve" (Ryan and Gross, 1943; Valente and Rogers, 1995). In 1962, Professor Everett Rogers of the University of New Mexico published a book entitled *Diffusion of Innovations* based on a large

number of cases, and proposed the famous "*S*-curve" theory of innovation diffusion. According to the diffusion speed, Rogers (1962) classified the diffusion of innovation into five categories: Innovators, Early Adopters, Early Majority, Late Majority and Laggards. The diffusion process of innovation was also divided into five phases: Knowledge, Persuasion, Decision, Implementation, and Confirmation. Coincidentally, in the 1960s, as the initial stage of international technology transfer, the theory of innovation diffusion was gradually introduced into innovation economics to study the effects of technology transfer on economic growth (Santacreu, 2015). It is not hard to see that here, the speed of innovation captures the proliferation of technology or knowledge at the individual, organizational, regional and national levels (Markman et al., 2005). The faster the speed, the higher the return.

The product lifecycle theory was first proposed by Harvard University professor Vernon in his article on *International Investment and International Trade in the Product Cycle* (Vernon R.,1966). Product lifecycle theory describes the entire process from when the product enters the market until it is finally eliminated (Vernon, 1966). The sales speed will determine the product's market share and corporate profits. As more and more companies recognize the importance of accelerating operations to establish competitive advantage, especially in industries with short lifecycles (Dumaine, 1989; Brown and Karagozoglu, 1993; Page, 1993), time competition has become an effective way for firms to increase profit and market share while controlling costs and market risks (Kessler and Chakrabarti, 1996). Obviously, innovation speed within a management perspective has examined competitive behavior at the organizational level. Here, speed refers to the rate at which discoveries are converted into profits. Fast innovators have been found to have greater revenue returns.

Innovation is also limited by time and depreciates quickly, so time is considered a scarce resource in the innovation process (Lawless and Anderson, 1996). The research on innovation speed originated in the late 1980s and early 1990s. Mansfield (1988) defined the speed of innovation as the time from initial development to final commercialization (the product is about to enter the market). Kessler and Chakrabarti (1996) defined the speed of innovation as a process from the initial discovery to the potential commercialization, which has also been widely accepted by later scholars (Markman et al.,2005). There is a growing recognition that innovation speed is important to a firm's creating and sustaining competitive advantage amidst rapidly changing business environments. In recent years, as the definition of product innovation speed is ambiguous, research on the speed of innovation using patent transfer or patent licensing has gradually emerged (Hegde, 2014; Drivas et al., 2016; McCarthy and Ruckman, 2017). At present, research on the speed of innovation mainly focuses on two aspects: one is the influencing factors (Wonglimpiyarat, 2005; Heirman and Clarysse, 2007; Goktan and Miles, 2011; McCarthy and Ruckman, 2017), and the other is the effects (Markman et al.,2005; Carbonell and Rodriguez, 2006; Zehir and Özşahin, 2008).

In fact, with the explosive growth of research on innovation speed, the fear of over-pursuing the speed of innovation is also being highlighted (Gans, 2008; Allain et al.,2011; Mauleon et al., 2013). In the patent trading market where it takes time for both

parties to reach an understanding and it also takes time for the technology to be properly valued, the licensor and the licensee are usually advised to spend more time before signing the contract. In other words, while speedy licensing might result in quicker returns, this could happen at the risk of a hurried sub-optimal deal and a lower price that results in a negative impact on both parties' earnings (Kessler and Chakrabarti, 1996). Unfortunately, most of these assessments originated from theoretical derivation, lacking sufficient theoretical foundation and empirical evidence, and are therefore seen as hoopla (Markman et al., 2005).

In summary, while research has provided valuable insights on the positive and negative effects of the speed of technology transfer both at organization-level and region-level, the function and theory of innovation speed in economic growth at city-level are not yet well understood. A key question is how to distinguish fast from slow innovation processes. Moreover, it is difficult to obtain technical transfer data at a city-scale. Our fundamental premise is that technology transfer has a positive effect on city economic growth. We distinguish fast from slow speed by identifying commercialization time from application to transaction of patent. We then assess a series of spatial panel data econometrics models and try to answer the question: is faster really better?

3. Method

3.1 Data

Transfer records exist for the legal status of patents. The Patent Search and Analysis Database (PSAD) of the State Intellectual Property Office of China (SIPO) has been tracking and recording the legal status of each patent since 2001. The data here is derived from this, and downloaded via a Python script. Due to the incomplete record of the initial period, our data period is from 2005 to 2015.

This paper only focuses on the patent transfer within mainland China, the sample does not refer to international technology transfers between overseas and mainland China, between Hong Kong, Macao, Taiwan (HMT) and mainland China, between overseas and HMT. In addition, there are some patent transfer records whose transferor and receiver addresses are not recognized. In total, 438,606 patent transfer records were retained while those international data and those missing owner were dropped (see table 1).

Table 1. Number of patent transfer in China from 2005 to 2015

Year	Initial data	International data	Unrecognized data	Final data
2005	18,963	12,239	761	5,963
2006	24,017	16,701	594	6,722
2007	38,226	27,013	682	10,531
2008	28,441	8,505	435	19,501
2009	33,569	9,817	477	23,275
2010	42,518	10,196	253	32,069
2011	59,519	12,924	206	46,389

2012	70,971	15,490	126	55,355
2013	88,407	15,503	77	72,827
2014	91,924	14,643	202	77,079
2015	117,069	28,000	174	88,895

According to the records of patent transfer, the construction of technology transfer database at city-scale is a tedious process and forms the core of this article. Our approach is based on the zip code of the transferor and the assignee's address. By associating the zip code with the administrative division code issued by the National Bureau of Statistics of China (NBSC), we successfully constructed a patent transfer database for cities within mainland China.

For each city, its patent transfer can be divided into external (input and output) and internal according to direction. As shown in Table 2, cities with high technology transfer are mostly located in the eastern coastal areas. Beijing, Shenzhen, and Shanghai have gradually become the three largest cities in mainland China for patent transfer. Overall, internal transfers account for the major part compared to external transfers, showing that technology transfer mainly serves the local economic growth of the city. On the other hand, it seems to confirm that technology transfer activities also follow geographical proximity (Sun and Grimes, 2017), which is not the topic to be discussed in this paper. However, in terms of input and output, the distribution pattern is quite different.

Table 2. Top 10 cities and its umber of patent transfer in 2005, 2010 and 2015

2005				
City	Total	Internal	External	
			Input	Output
Foshan	1,014	911	34	69
Beijing	837	477	203	157
Shanghai	745	389	187	169
Ningbo	384	365	14	5
Shenzhen	327	178	90	59
Guangzhou	287	170	59	58
Shenyang	242	45	96	101
Nanjing	191	142	8	41
Hangzhou	160	125	23	12
Chongqing	150	123	10	17
2010				
City	Total	Internal	External	
			Input	Output
Beijing	3,501	2,109	490	902
Shanghai	3,389	2,299	492	598
Changsha	3,169	3,076	40	53
Shenzhen	2,102	1,196	430	476
Ningbo	1,394	1,225	65	104
Tianjin	1,070	404	217	449

Hangzhou	1,042	726	147	169
Dongguan	1,015	767	117	131
Guangzhou	977	586	204	187
Suzhou	894	483	317	94

2015

City	Total	Internal	External	
			Input	Output
Beijing	12,483	7,211	2,954	2,318
Shenzhen	10,223	5,736	2,172	2,315
Shanghai	7,354	3,704	1,807	1,843
Suzhou	4,456	1,993	836	1,627
Guangzhou	4,148	2,224	1,073	851
Ningbo	3,288	1,653	434	1,201
Hangzhou	2,984	1,394	649	941
Dongguan	2,688	1,402	642	644
Nanjing	2,578	1,142	573	863
Qingdao	2,532	1,079	910	543

3.2 Variables

Our study focuses on examining the impacts of patent transfer speed on city economic growth. Therefore, the dependent variable is the level of city economic development, which is a popular indicator used in economics and is measured as the gross regional product (*GRP*). The data of GRP is from the Chinese Statistics Yearbook (2006-2016).

Existing research has examined the duration and timing of the patent application (Gans, 2008). Based on McCarthy and Ruckman's (2017) work, speed here is measured as the number of years between the application for a patent and the signing of a transfer agreement. To distinguish between fast from slow, we divide the speed into four levels. The first level is no more than one year, that is, the duration from the application to the transfer of a patent does not exceed one year, which is abbreviated as *One-year*. The second is *Two-year*, which means that the duration is more than one year but not more than two years. The third is more than two years but less than five years, which also is abbreviated as *Five-year.* The last is more than five years, which is abstracted as *Upfive-year*. In summary, there are four explanatory variables in here, respectively, *One-year*, *Two-year*, *Five-year*, and *Upfive-year*, and each explanatory variable is calculated by the transferring number of patents at the corresponding speed.

Furthermore, we also add three control variables. First is the total number of employees in each industry (*Labor*), the second is total investment in fixed assets (*TIFA*) and the third is foreign direct investment (*FDI)*. In economic growth theory, both the neoclassical economic growth model (Solow model) and the endogenous economic growth model (Romer model), labor and capital are the two fundamental variables (King and Rebelo, 1993).For capital variables, the positive effects of the two variables, *TIFA* and *FDI*, on city economic growth have been widely confirmed (Su and Liu, 2016; Chen et al., 2017).

3.3 Statistical method

We use a series of panel regression models (e.g., random effect model, fixed effect model and mixed effect model) to test whether innovation speed has full or partial effects on city economic growth. We also perform a double-hierarchical regression to test the hypothesis. First, we normalize the four speed variables, and use the average speed of city technology transfer as an independent explanatory variable (*Ave-speed*) to construct the regression model I. Second, we input the four speed variables simultaneously to construct the regression model II. In both models, we also enter the three control variables at the same time.

In addition, after a series of tests including *LM*-test, *F*-test and *Hausman*-test, were compared with the mixed effect model, the random effect model and the fixed effect model, we found that the two-way fixed effect model is more suitable and is therefore used in this paper.

4. Results

In terms of the data, variables, and statistical method, first of all, the spatial evolutionary pattern of innovation speed in China is mapped. Second, this paper generates the two-way fixed effect model to identify relations between innovation speed and city economic growth.

4.1 Mapping the speed pattern

Before testing the relations, we present the spatial evolutionary pattern of the innovation speed of technology transfer though visualization (Table 3 and Figure 1). In 2005, the average speed of city technology transfer in China was 2.956 years, and rose to 3.287 years in 2010, and also dropped to 2.899 years in 2015. Generally, cities with rapid speed of technology transfer in China were mostly located in the central and western regions.

Table 3. Top 10 cities with higher speed in patent transfer in 2005, 2010 and 2015

Rank	2005		2010		2015	
	City	*Ave_Speed*	*City*	*Ave_Speed*	*City*	*Ave_Speed*
1	Ji'an	1.000	Liaoyuan	1.000	Shuangyashan	1.375
2	Jincheng	1.000	Guang'an	1.000	Panzhihua	1.386
3	Pingxiang	1.000	Anqing	1.417	Dazhou	1.418
4	Shangrao	1.000	Jingdezhen	1.417	Maoming	1.449
5	Shuangyashan	1.000	Jincheng	1.500	Shaoyang	1.456
6	Yongzhou	1.000	Baishan	1.500	Zhangjiajie	1.567
7	Heyuan	1.400	Zaozhuang	1.785	Suizhou	1.669
8	Bayannur	1.500	Pingxiang	1.792	Neijiang	1.696
9	Chaozhou	1.500	Tieling	1.848	Huaihua	1.698

10	Guang’an	1.500	Meishan	1.875	Huaibei	1.704

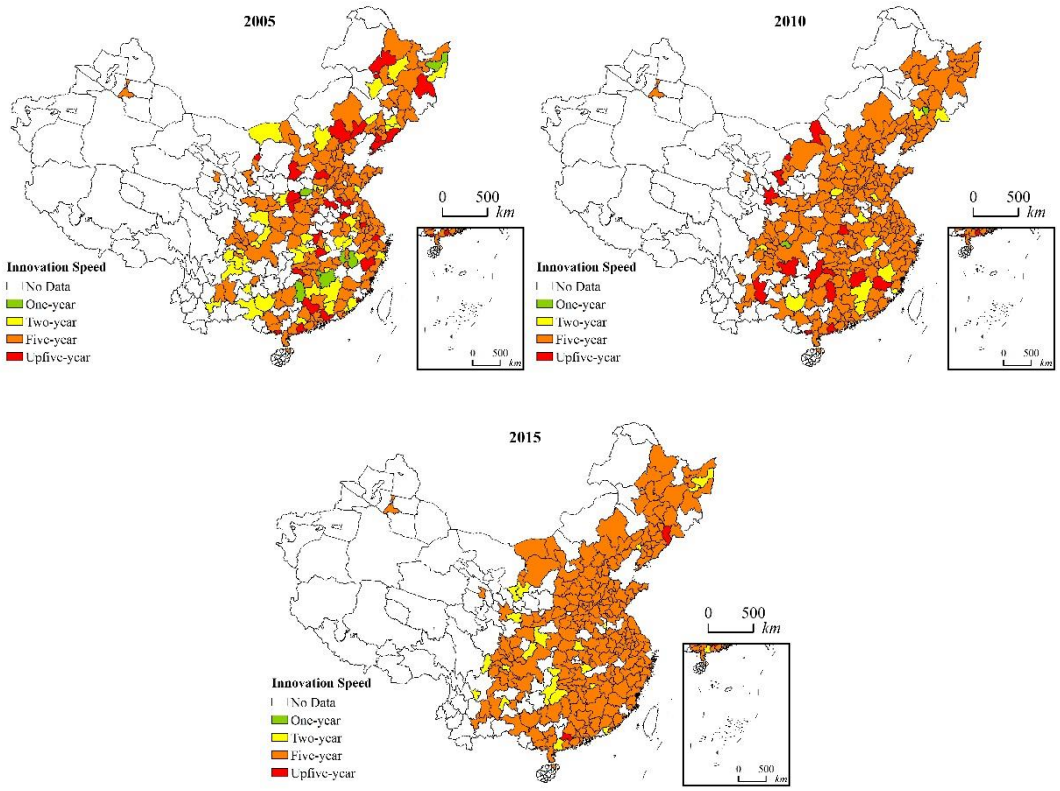

Figure 1 Spatial evolutionary pattern of average speed in technology transfer in China

Specifically, in 2005, there were 6 cities with an average speed of no more than one year, and three of them were located in Jiangxi Province, namely Shangrao City, Pingxiang City, and Ji’an City. The other three cities were Shuangyashan City in Heilongjiang Province, Yongzhou City in Hunan Province and Jincheng City in Shanxi Province. Second, there were 42 cities whose average speed was between one year and two years. Most of these cities were also located in the central and western regions of China. Analysis finds that the scale of technology transfer in these cities was relatively small, only accounting for 2.92% of the total. The technology transfer speed in cities in the eastern regions was generally slow. Cities such as Beijing, Shanghai, and Shenzhen had an average speed of 3 to 5 years. Although the speed in the central and western regions was relatively fast, cities with a transfer speed of more than five years (with a total of 27) were also mostly located in the central and western regions. The patent transfer scale of these cities was also small, just accounting for 2.32%.

In 2010, the number of cities in the first two levels has been significantly reduced. There were only 2 cities with technology transfer speed of less than one year, respectively, Liaoyuan City in Jilin Province and Guang’an City in Sichuan Province. The number of cities whose technology transfer speed were between 1 and 2 years has also dropped to 15. Technology transfer in these 17 cities accounted for only 0.29% of the overall. These cities were still located in the Midwest. This year, the scale of technology transfer in most cities expanded rapidly. Correspondingly, the speed of technology transfer also increased. The number of cities with technology transfer speed

of more than 2 years has reached 220, of which 17 cities have experienced technology transfer speeds of more than 5 years.

In 2015, the vast majority cities in technology transfer generally took two to five years. There were 21 cities with technology transfer speed of no more than two years, and there are only 2 cities with more than five years of transaction. On the whole, the spatial distribution pattern of the innovation speed of technology transfer was more balanced, while the faster cities were still mainly distributed in the central and western regions.

4.2 Regression results

Table 4 shows the variable measures and descriptive statistics, indicating the diversity of technology transfer speed included in the sample. Even though we only divide the speed into four levels, there is considerable range for the variables. The correlation matrixes for Model I and Model II are in Table 5, and the regression results of the two-way fixed effects model are in Table 6.

Table 4. Descriptive statistic of variables

Variable		Measure	Mean	Std.
Explained variable	GRP	Level of city economic development measured as the gross regional product	17,300,000	24,000,000
Control variables	Labor	Total number of employees in each industry	53.7	77.5
	Capital	Total investment in fixed assets	10,500,000	12,900,000
	FDI	Foreign direct investment	76,127	175,225
Explanatory variables	Ave-Speed	Average speed of city technology transfer	3.02	1.37
	One-year	Number of patents that have been transferred with the speed of no more than one year	106	419.6
	Two-year	Number of patents that have been transferred with the speed of more than one year but no more than two years	82.29	262.9
	Five-year	Number of patents that have been transferred with the speed of more than two years but no more than five years	105.3	379.9

Upfive-year	Number of patents that have been transferred with the speed of more than five years	26.05	106

Table 5. correlation matrix of Model I and Model II

Model		Variable	1	2	3	4	5	6	7	8
Model I	1	GRP	1							
	2	Labor	0.869***	1						
	3	Capital	0.861***	0.762***	1					
	4	FDI	0.864***	0.762***	0.803***	1				
	5	Ave-Speed	-0.047**	-0.047**	-0.037*	-0.048**	1			
Model II	1	GRP	1							
	2	Labor	0.869***	1						
	3	Capital	0.861***	0.762***	1					
	4	FDI	0.864***	0.762***	0.803***	1				
	5	One-year	0.776***	0.728***	0.541***	0.622***	1			
	6	Two-year	0.823***	0.757***	0.597***	0.666***	0.938***	1		
	7	Five-year	0.810***	0.750***	0.568***	0.655***	0.940***	0.957***	1	
	8	Upfive-year	0.772***	0.727***	0.532***	0.629***	0.912***	0.900***	0.963***	1

Note: N=246, $^{*}p<0.1$, $^{**}p<0.05$, $^{***}P < 0.01$.

Table 6. Two-way Fixed effects model of panel regression.

	Model I				Model II			
GRP	Coef.	Std.Err.	t	p>|t|	Coef.	Std.Err.	t	p>|t|
Labor	69445.530	42296.550	1.640	0.102	23704.800*	13944.990	1.700	0.090
Capital	0.735***	0.156	4.710	0.000	0.745***	0.069	10.820	0.000
FDI	28.359*	13.9.6	2.040	0.042	10.972**	5.556	1.970	0.049
Ave-Speed	-11989.250	35932.860	0.330	0.739	/	/	/	/
One-year	/	/		/	1162.323	1492.617	0.780	0.437
Two-year	/	/	//	/	8595.399**	3582.968	2.230	0.027
Five-year	/	/	/	/	7687.801	4947.835	1.550	0.122
Upfive-year	/	/	/	/	13174.800	8556.520	1.540	0.125
2006	653021.90***	148724.800	4.390	0.000	693851.80***	103259.500	6.720	0.000
2007	1311741***	231005	5.680	0.000	1376049***	179219	7.680	0.000
2008	2082461***	337253.200	6.170	0.000	1839193***	210160	8.750	0.000
2009	1890668***	587185.300	3.220	0.001	1587891***	282432.200	5.620	0.000
2010	2705596***	833935.900	3.240	0.001	2197498***	417983.100	5.260	0.000
2011	4553971***	901213.700	5.050	0.000	3712050***	406318	9.140	0.000

2012	4402988***	1054113	4.180	0.000	3688407***	462449.800	7.980	0.000
2013	3621706**	1436696	2.520	0.012	2768639***	565572.600	4.900	0.000
2014	3398271**	1695262	2.000	0.046	2308905***	622433.500	3.710	0.000
2015	4126139**	2005153	2.060	0.041	2501716***	786155.100	3.180	0.002
_cons	1098357	2061505	0.530	0.595	3311293***	739612.500	4.480	0.000

Note: N=246, $^{*}p<0.1$, $^{**}p<0.05$, $^{***}P < 0.01$.

Table 5 shows that in Model I, there are significant positive correlations between the three control variables and the explanatory variables, which verifies the relevant conclusions in the field of city economic growth (King and Rebelo, 1993; Su and Liu, 2016; Chen et al., 2017). And there is a significant negative correlation between the explanatory variables and the explained variables, which also confirms the findings of the innovation speed theory (Kessler and Chakrabarti, 1996; Shan et al., 2016). In Model II, the four explanatory variables measured by the number of transferred patents under each speed show a significant positive correlation with the level of city economic development.

Table 6 shows that, as we expected, the average speed for technology transfer is inversely proportional to the level of city economic growth (in Model I, the coefficient of Ave-Speed is less than 0), that is, the shorter the time spent, the faster the city's economic growth. Unfortunately, it does not pass the test (p>0.1), indicating that when the speed of technology transfer reaches a certain critical value, this inverse relationship may show reverse characteristics.

The regression results of Model II just confirm the results of Model I. By dividing the innovation speed into four levels, we find that although the number of transferred patents at the corresponding speed has a positive relationship with the city economic growth, only the variable of Two-year shows the significant correlation. In other words, the One-year, representing the fastest speed, and the Five-year and Upfive-year representing the slower speeds do not pass the significance test, which indicates that for city economic growth, the speed of technology transfer is not the faster the better. This also supports some doubts about the speed of technology transfer in academia. That is, excessive technology transfer leaves the technology owner with insufficient time to fully evaluate the value of the technology, and there is also not enough time for licensors to assess whether the assignees have enough capacity to commercialize this technology, thus making the technology wasteful without full development (Allain et al., 2011).

5. Discussion and conclusions

In order to understand the speed effects of technology transfer, this present paper attempts to propose a speed effect hypothesis from the city scale. That is, technology transfer realizes the macroscopic appearance through the microscopic self-interest mechanism, thus serving city economic growth. In this study, we examined the continuing hotly discussed issue in the field of innovation speed: is faster really better?

Innovation economics widely believes that the faster the technology transfer, the greater the return to the transferor. Although there has been some skepticism in recent years that excessive speed may be counterproductive, it has been condemned by the innovation speed admirers for lacking empirical evidence. This study of the speed effects of China's city technology transfer answers this questioning effectively. Thus, there may be a threshold for the speed of city technology transfer, which is most suitable for 1 to 2 years, but the evidence is very weak.

The research findings may have new implications for policymakers. In the current policies of Chinese local governments promoting technology transfer, the arguments for accelerating technology transfer are invariably heard, and often appear in government documents or headlines of the news media. The government's excessive emphasis on the speed of technology transfer may be counterproductive. The regression results indicate that technology transfer which only maintains a relatively rapid speed can promote city economic growth. However, based on the current average speed of China's technology transfer, it is still necessary to appropriately accelerate this in the coming period.

This paper contributes to the existing literature in two ways by dividing the speed of technology transfer into four levels from the city scale. The first is to understand the evolution pattern of technology transfer at the city scale. Due to the availability of data, a large number of spatial-level technology transfer studies focus on the regional (provincial) scale (Drivas and Economidou, 2015; Wang et al., 2015; Zhang et al., 2016), and few of them have involved the city scale. Based on the data mining with Python script, this study discusses the technology transfer problem at the city scale from the perspective of patent transfer. The second contribution was to examine the non-linear relationship between the speed of technology transfer and city economic growth through panel regression models. Although the existing studies questioned the simple positive correlation between the speed of technology transfer and the benefits (Allain et al, 2011; Mauleon et al, 2013), there was very little detailed evidence. This method of distinguishing fast from slow speed provides a new perspective for studying the relationship between innovation speed and revenue.

Four limitations should be considered for future studies. Firstly, we only studied the relationship between the speed of technology transfer and city economic growth in China from 2005 to 2015. Therefore, our contribution mainly provides an hypothesis. In order to verify these findings, it is also necessary to conduct continuous follow-up research on China's city technology transfer, or to study cases in other countries. If we could find some similar results, it may be more fruitful for the development of technology transfer policies. Secondly, in order to distinguish between fast and slow, this article divides the speed of technology transfer into four levels, which appears to

be simple. In order to deepen our approach, we should divide the speed of technology transfer into more levels so that we can more precisely study the relationship between innovation speed and benefits. Thirdly, this article only uses the patent transfer to construct the technology transfer system at the city-scale. Therefore, our contribution is more of a sample study. If we combine more ways of transferring technology (such as patent licensing) and get similar conclusions, this conclusion would be more persuasive. Lastly, as we know, the speed of city technology transfer is affected by many factors, among which the level of city economic development is a major factor. Therefore, the interaction mechanism between the speed of technology transfer and the level of city economic development can also be a focus of future research.

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